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Modeling and forecasting Value-at-Risk in the UAE stock markets: The role of long memory, fat tails and asymmetries in return innovations

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Abstract

In this paper, we investigate the adequacy of the FIAPARCH class of GARCH models to measure value at risk (VaR) in the UAE stock exchanges. Our empirical results show that accuracy is improved when VaR is computed using innovations modeled as t skewed distribution. Including a long memory in the conditional volatility process would also improve the results. We conclude that, the modeling of asymmetry, fat tails and long memory have potentially important implications for risk assessment, and hedging strategies in the UAE stock exchanges.

Key Words: Value-at-Risk, long memory, fat tails, UAE stock exchanges.

1. Introduction

In recent years, risk measurement has received considerable attention. One measure of risk that became popular was Value at Risk (VaR here in after). After the Basel Committee for banking supervision, VaR has become a basic ingredient in the computation of capital charges for compliant banks. According to Basel, banks have to provide capital to protect against market risk exposures in its trading portfolios. These capital charges are computed as a percentage of a multiple of the VaR measure. In addition, a VAR system can be used to monitor and control exposures, as well as for risk budgeting and allocation.

The VaR measure is an easy to work with approach for risk measurement, and management. It is widely recognized and understood by portfolio managers, and practitioners. Moreover, VaR provides a single quantity that summarizes the overall market risk faced by an institution. The VaR measure is defined as the minimum losses that could arise in the normal course of business from changes in market prices. More precisely, VaR is the estimated portfolio loss that a stock or portfolio is unlikely to exceed, over a given time horizon, at a given probability level. The VaR measure can be used by financial institutions to calculate the minimum capital requirements needed to protect against market risks[1].

As mentioned above, the VaR measure is the quantile of the return distribution, therefore, an adequate modeling of the tails is vital for unbiased estimation. This is specifically true in non-normal financial return distributions, which exhibit skewness and excess kurtosis. Another stylized fact that should be accounted for is volatility clustering and long memory. The empirical evidence has indicated that ignoring these stylized facts, would lead to a downward biased measure of risk[2].

Several models have been proposed in the literature to account for stylized facts in asset returns. For instance, the GARCH model of Bollerslev (1986) allows for time-varying volatility, and it is able to produce leptokurtosis in asset returns distribution. However, in this model, only the magnitude of the shock, and not its sign, affects the conditional volatility. Hence, the model fails to capture another stylized fact, namely, asymmetry in the return distribution and this leads a VaR estimates that are downwardly biased. This limitation has been avoided by proposing extensions of the original GARCH model, such as the exponential GARCH model of Nelson (1991) (the EGARCH model), and the asymmetric power ARCH of Ding et al. (1993) (the APARCH model).

Another empirical fact that these models fail to accommodate, is the long memory in market volatility. This shortcoming has led to a class of specifications that allow volatility to be modeled as a fractionally integrated process, with a slow decay in its autocorrelation function. A particular group of models in that direction is the Fractionally Integrated Asymmetric Power ARCH (the FIAPARCH here in after) model first proposed

[1]Market risk is defined as the loss induced by changes in market prices: interest rate, stock, foreign exchange and commodity prices.

[2] See e.g., Giot and Laurent (2003), So and Yu (2006), Bali and Theodossiou (2007), Angelidis (2007), Haas (2009), among others.

by Tse (1998)[3]. This model is flexible, and able to capture asymmetry, as well as long memory in financial time series.

The literature on the effects of these stylized facts on the estimation of risk is plenty. For instance, Fernandez and Steel (1998) have shown the improved performance of the skewed Student-t distribution that allows for fat tails in the return innovation. Also, Lambert and Laurent (2000, 2001) have recorded an improvement by using the skewed t distribution in the context of a GARCH framework. A multiple of studies have estimated VaR for stock indices using FIAPARCH model with a skewed Student-t distribution, and all have pointed outperformance compared to a normal-GARCH model[4]. These models were found to be adequate in capturing fat-tails, volatility clustering, asymmetry, and long-memory in return distribution.

The literature on VaR in the context of emerging markets has also stressed the importance of asymmetry and long memory. The skewed return distribution for the VaR accuracy in Southeast Asian economies has been stressed by Brooks and Persand (2003). Similarly, McMillan and Speight (2007) have concluded that both asymmetry and long memory are important consideration for risk measurement in eight of the emerging stock markets[5].

The extensive research on the modeling and forecasting VaR has focused on well-developed markets, and to a much lower extent, on some important emerging markets that has large market capitalization. To our best knowledge, we found no evidence that covers the measurement of risk in the UAE stock exchanges.

The UAE stock markets are composed of two markets: the Abu Dhabi Securities Exchange (ADSE), and the Dubai Financial Market (DFM). These markets have been one of the fastest-growing stock markets in the Middle East. The total market capitalization of both markets has grown from US$ 29.7 billion at the end of 2002 to six folds (US$ 167.6 billion) by the end of 2006. It then declined sharply to US$ 131.8 billion following the recent financial crisis in 2008. These exchanges are well integrated with global financial markets and restrictions on foreign capital flows are minimal.

As the size of these markets is small compared to big exchanges, these markets are sensitive to rebalancing decisions and worldwide portfolio adjustments of large investment houses. Moreover, the UAE is located in the politically unstable and oil dependent Middle East region, and that introduces other risk factors that may make these markets more volatile compared to other exchanges. Consequently, these markets may be more risky than other well-established, as well as, other emerging stock exchanges[6].

[3]For a survey of ARCH processes see Bera and Higgins (1993), Bollerslev et al. (1994), Gouriéroux (1997), Li et al. (2001), Poon and Granger (2003), Degiannakis and Xekalaki (2005), Bauwens et al. (2006), and Angelidis and Degiannakis (2008).

[4] See, Giot and Laurent (2003, 2004), Degiannakis (2004), Angelidis and Degiannakis (2005), Bali and Theodossiou (2006), Angelidis et al. (2007), and McMillan and Kambouroudis (2009).

[5] For emerging market evidence see also Brooks and Persand (2003), Yong et al. (2006), Lee et al. (2006), Ender and Knowles (2006), McMillan and Speight (2007), Cheong (2008), Angelidis and Benos (2008), McMillan and Kambouroudis (2009), Ouygan (2009).

[6] There is evidence that these markets are less information ally efficient compared to developed markets. Poor-quality of information, high trading costs, and less competition may increase inefficiency (See Assaf, 2009). This environment may contribute to a different behavior than that observed in developed stock exchanges.

The objective of this paper is to assess the performance of FIAPARCH, in measuring and forecasting VaR in UAE stock markets. The paper considers both long and short daily trading positions of the two market indices: the ADSE index and the DFM index. Although, institutional and individual investors may not hold portfolios that replicate the index, still the first step in their strategic asset allocation would be to develop capital market expectations of both risk and return at the level of the aggregate market. Hence, the paper provides evidence on risk in the UAE stock exchanges, for those investors who are interested to implement a top down approach to their strategic asset allocation. This may be useful for funds seeking international diversification, or for global macro hedge funds or a fund that seeks an exposure to emerging markets. In the particular case where the interest lies in a bottom up approach, the analysis at the level of the individual stock becomes necessary and we leave the risk assessment of that to another paper[7].

In the FIPARCH model, we consider innovations that follow three different distributions: the normal, Student-t, and skewed Student-t distribution innovations[8]. We then aim at evaluating predictive accuracy of the model when introducing different distributions, under a risk management framework. To test VaR accuracy of the model under different specifications of the error we back test using two tests: the unconditional coverage (the LR here after) test of Kupiec (1995) and the dynamic quantile (the DCQ here after) test of Engle and Manganelli (2004).

The contribution of this article is twofold: first, we implement the empirical analysis of VaR on the UAE stock markets using daily returns of the indices. To our best knowledge, this line of research has not been applied to the UAE exchanges. Second, we assess the risk model for both long and short trading positions. This sheds some lights on the difference between risk exposures of long and short positions in skewed return distributions.

The remainder of this paper is organized as follows. In Section 2, we describe the UAE stock exchanges. The exposition of the data description and the methodology are outlined in Section 3. In Section 4, we present the empirical results, and finally Section 5 includes some concluding remarks.

2. The UAE Financial Markets

The UAE markets contain two stock exchanges: the Abu Dhabi Securities Exchange (ADSE) and the Dubai Financial Market (DFM). A small fraction of the market capitalization of individual stocks is also traded over-the-counter. The two markets are fully electronically linked, allowing investors to place orders for stocks through brokers in either exchange. The two markets settle trades using different number of trading days, the ADSM uses T+1 convention, while the DFM employs a T+2 settlement basis.

The ADSE began operations in November 2000. In nine years, the number of listed companies has increased to 67 with a market capitalization of US$ 72,967.81

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[7] The authors would like to thank one of the referees for pointing out that there is also an interest in risk assessment of individual stocks.

[8] It has been argued by So and Yu (2006) that the distribution has a larger impact than the volatility model for the VaR forecast.

billion (See Table 1). Most of market capitalization belongs to services, investment and banking sectors, with other sectors contributed minimally to the market value. Moreover, trading volume has grown steadily over the past five years, going from US$ 363.08 million in 2002 to US$ 18,698.35 billion in 2009. The increase in trading volume was the result of the increased listing. The IPOs and the stock splits have also contributed to a larger trading volume.

Table 1: The UAE Financial Markets

	2002	2004	2006	2008	2009
Number of Listed Companies					
ADSE	24	35	60	65	67
DFM	12	18	46	57	65
Market Capitalization (million $)					
ADSE	20,375.76	55,490.40	80,744.76	61,887.63	72,967.81
DFM	9,469.52	35,090.90	86,894.83	65,217.73	58,829.91
Value Traded (million $)					
ADSE	363.08	4,449.14	19,221.64	61,297.80	18,698.35
DFM	687.80	13,735.05	94,735.46	69,876.87	46,659.87
Turnover Ratio (%)					
ADSE	1.78	8.02	23.81	99.01	25.6
DFM	7.26	39.14	109.02	107.14	79.3

Source: Arab Monetary Fund, AMDB.

The DFM also began its operations in March 2000 as a securities trading market, before expanding to a full-fledged exchange. The DFM was initially expected to operate as a secondary market for trading securities issued by public companies, and for bonds issued either by the government, or by the financial and investment institutions. By the end of 2009, the number of listed companies was 65 with a market capitalization of US$ 58,829.91 billion (See Table 1). Trading volume has also grown rapidly over the past five years, going from US$ 687.8 million in 2002 to US$ 46,659.87 billion in 2009.

3. Data and Methodology

3.1 Data description

The data used for this study are obtained from the ADSE and DFM. The data includes daily closing price of indices for both the ADSE and DFM. The sample extends from December 31, 2003 to June 30, 2009 for a total 1375 observations. The sample period was determined primarily by the availability of data in the markets[9]. We compute and analyze the continuously compounded rate of return, $r_t = log(P_t/P_{t-1})$, where P_t denotes the index level in day t. The financial markets in the UAE construct these indices as capital weighted as opposed to other weighting schemes. A particular stock is included in the index if it has a percentage of free float that is greater than 5% of its total capital. The market capitalization of companies included should not exceed 25% of the total market capitalization of the index and hence, an individual company may not drive the dynamics of the index. The coverage of the indices is high in both markets, and they represent around 90% of the aggregate markets capitalization of listed companies.

[9] The data are obtained from the ADSE and DFM websites.

Figure 1 shows the daily levels and the continuously compounded return for both indices. As can be seen in the figure, volatility clustering is clearly visible. Figures (2) and (3) present the QQ-plot and Kernel density-plots, respectively. The figures show that the return series of both indices deviates from normality (See figure 2). Moreover, the fitted kernel density plot of returns exhibit skewness and fat tails as can be seen in figure 3. The imagining of the estimated density for the two indices using bivariate kernel further supports this finding (Figure 4).These characteristics of the indices indicate that the VaR model must account for volatility clustering, kurtosis and skewness at the same time.

Table (2) summarizes the descriptive statistics of returns. As can be seen in the table, both return series appear to have similar statistical properties. The skewness is negative and significant, implying a possible leverage effect in the data. The excess kurtosis is positive and significant indicating fat-tails. The null hypothesis of normal returns has been strongly rejected by J-B test of normality.

The Ljung-Box test for the levels and the squares indicates that index returns exhibit significant autocorrelations and that there exists a significant ARCH effects in conditional volatility[10]. To check more formally, we perform Engle's ARCH (1982) test. Again the resulting statistics are all highly significant, hence, the preliminary analysis of the data suggests that the GARCH class of models that capture asymmetry, fat-tails, and time-varying volatility is suitable for modeling the dynamics of the UAE return series.

The lower part of Table (2) presents tests results for the null of unit root. We present results for three tests: ADF, PP, and KPSS tests. As can be seen in table the null of unit root was significantly rejected in the ADF and PP tests. Similarly, the KPSS test fails to reject the null hypothesis of stationarity. These results suggest that the daily return series of the UAE markets are short memory stationary process.

The last three rows of the table provide tests for long memory in volatility. To apply the tests we used squared returns as well as absolute returns to proxy the latent volatility. The tests indicate that volatility is characterized by long memory (See Lo’s (1991) R/S test statistics)[11]. The tests also indicate that there is no evidence of long memory in returns.

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[10] Similar to most emerging markets, the existence of linear dependences in UAE returns indices may be attributed to thin trading problem.

[11] There is little theoretical justification to prefer one volatility measure over another. In this paper, we follow Bollerslev and Wiright (2000) in using the two volatility measures.

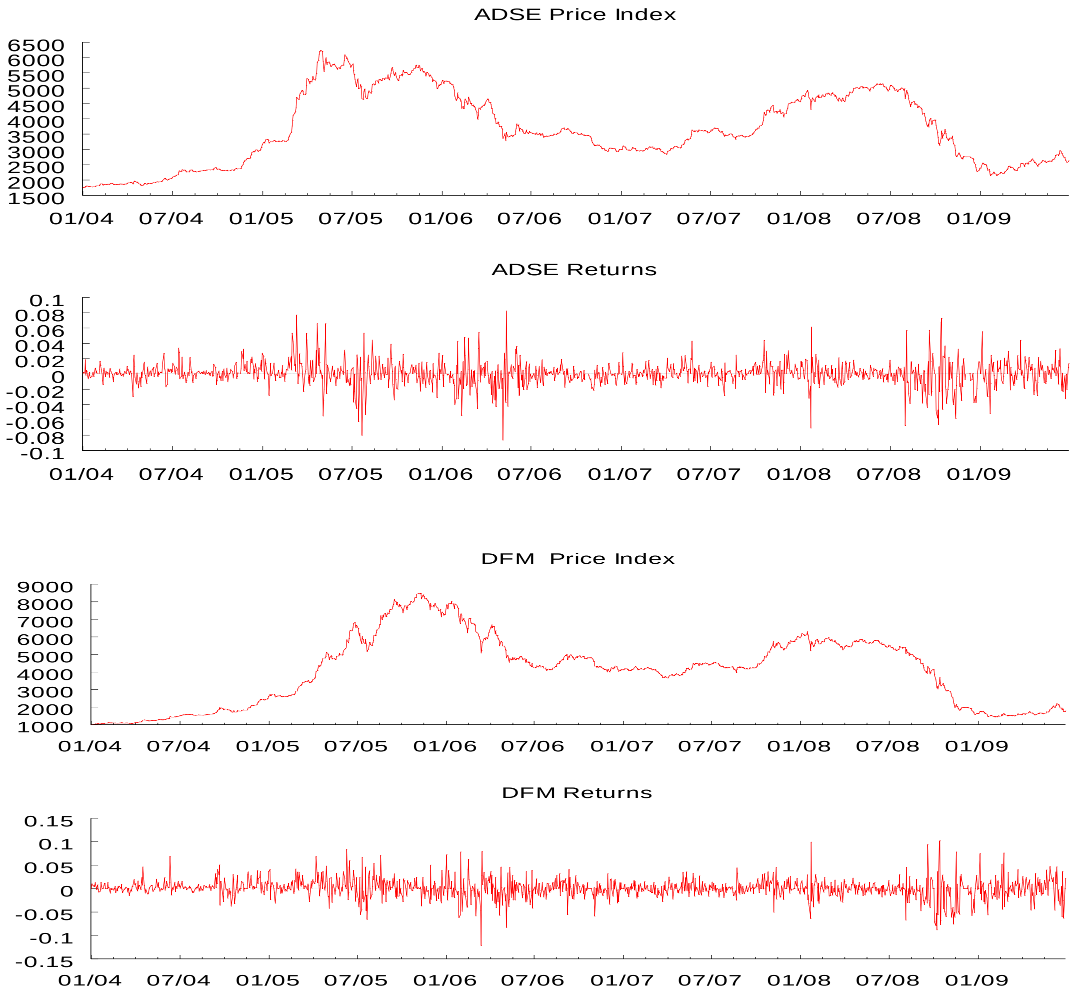

Figure 1. Plots of DFM and ADSE daily closing prices and returns.

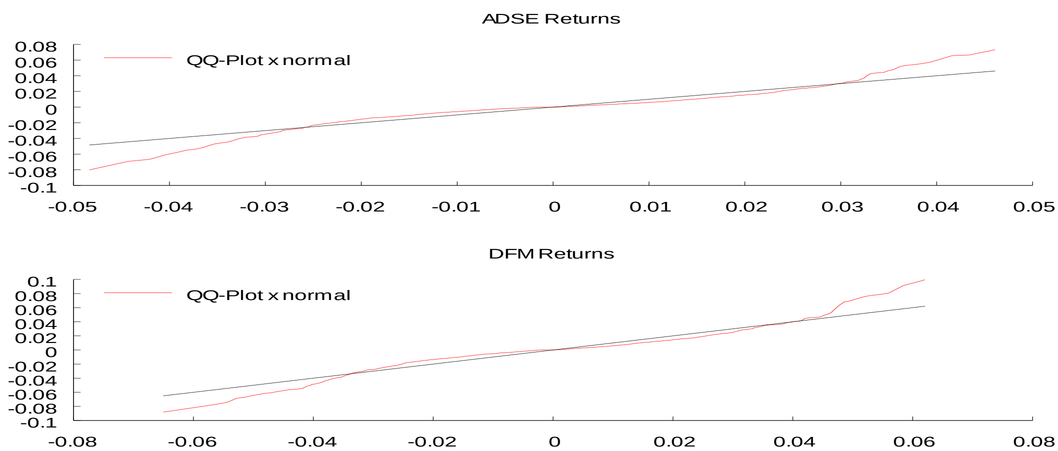

Figure 2. Quantile-quantile plots

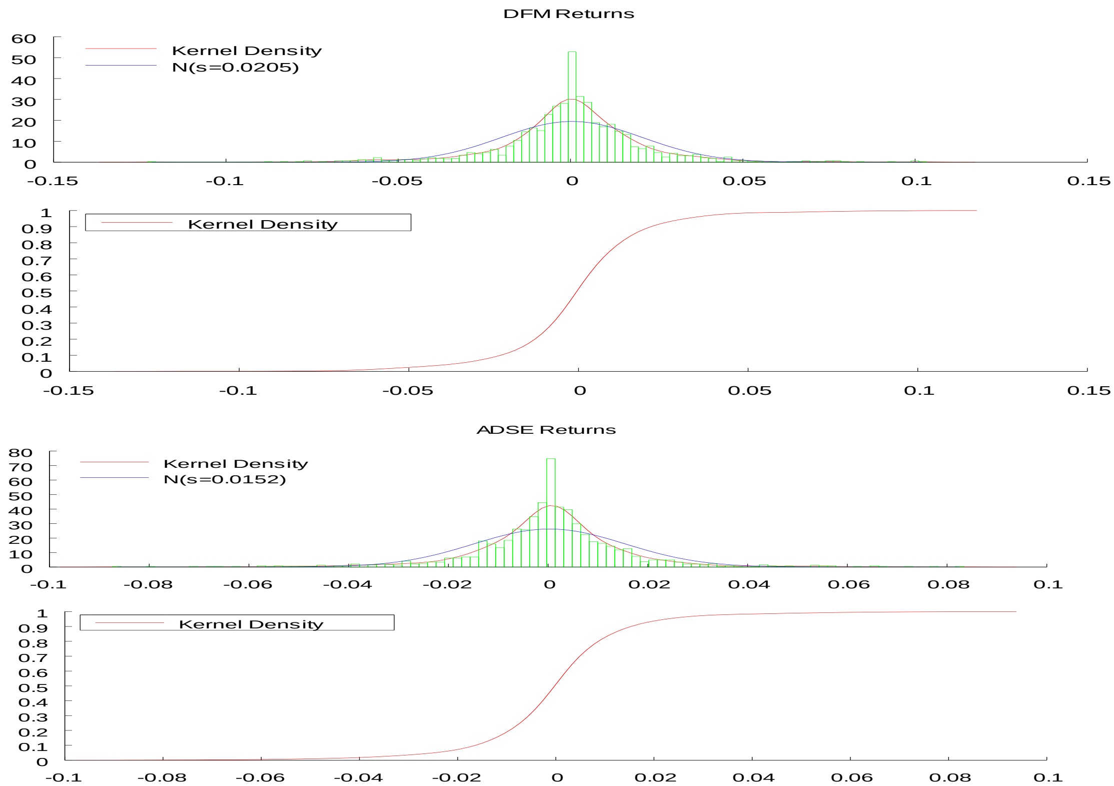

Figure 3. Kernel density plots

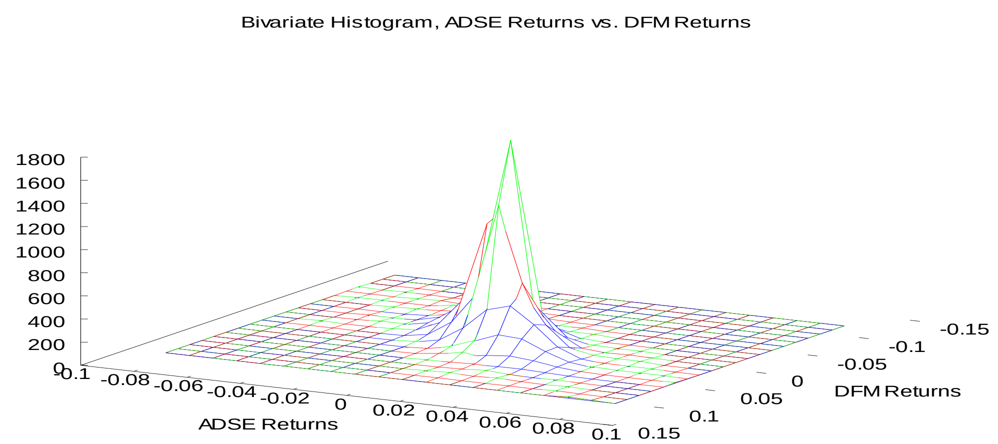

Figure 4. Normalized return index across the two markets.

Table 2: Descriptive statistics, ADF, PP, KPSS and Lo tests

	ADSE	DFM
Mean (%)	0.0122	0.0175
Maximum (%)	3.5820	-5.2798
Minimum (%)	-3.7562	-5.2798
S.D. (%)	0.6606	0.8890
Skewness	-0.0759	-0.0651
Kurtosis	5.6867	4.5336
J-B	1933.6*	1229.1*
	(0.0000)	(0.0000)
$Q(10)$	65.0517*	43.9277*
	(0.0000)	(0.0000)
$Q^2(10)$	369.170*	560.749*
	(0.0000)	(0.0000)
ARCH (10)	22.198*	30.388*
	(0.0000)	(0.0000)
ADF test statistics	-5.6213*	-8.3210*
	(0.0000)	(0.0000)
PP test statistics	-12.5482*	-14.5610*
	(0.0001)	(0.0001)
KPSS test statistics	0.3443 {<1}	0.0391 {<1}
Lo's R/S test statistics for r_t	0.1672	0.4472
	(0.4082)	(0.7178)
Lo's R/S test statistics for $\|r_t\|$	0.7264*	0.8701*
	(0.0001)	(0.0001)
Lo's R/S test statistics for r_t^2	0.7201*	0.8557*
	(0.0001)	(0.0001)

Notes: J-B is the Jarque-Be´ra (1980) normality test statistic. The test follows χ^2distribution with 2 degrees of freedom. r_t, $|r_t|$, r_t^2 are respectively log return, squared log return and absolute log return. $Q(10)$ and $Q^2(10)$ are the Ljung-Box Q-statistic of order 10 on the returns and squared returns, respectively. ARCH(10) is the test for conditional heterocedasticity in returns, which is based on the regression of squared residuals on lagged squared residuals. ADF is the Augmented Dickey-Fuller (1979) unit root test statistic. PP is the Phillips-Perron (1988) unit-root test statistic. KPSS is the Kwiatkowski, Phillips, Schmidt and Shin (1992) stationarity test statistic. The P-values are reported in brackets. * indicates significance at the 1% level.

3.2 Methodology

3.2.1. Value-at-Risk

The VaR measure, estimates the minimum loss in a bad day that result from an adverse movement in market factors. The stock market normally consists of investors who make profit during bull markets. Specifically, when a trader assumes a long position in a stock, the stock price needs to move up to make the position profitable. Therefore, the trader encountered risk when the price of the stock declined. On the contrary, if a trader enters a short position in a stock, then the price of the stock must decline in order for the trader to generate a profit. The risk in this particular case comes from a rise in the price of factor rather than from its decline. Therefore, in the first case we need to model the left tail of the return distribution, while in the second case, the need arise to model the right tail of the distribution.

In the sequel, let $\mathrm{r_t}$ be the returns of an asset or a portfolio with $t = 1, \dots, T$. Also Denote the cumulative distribution function (cdf) of $\mathrm{r_t}$ by $F_T(x)$, then the VaR for a long position over the time horizon T with confidence α may be defined as

$$F_L(VaR) = P\big(r_t \leq VaR_t(\alpha)\big) \qquad (1a)$$

Similarly, for short position, the VaR can be expressed as follows:

$$F_s(VaR) = P\big(r_t \geq VaR_t(\alpha)\big) = 1 - F_L(VaR) = 1 - \alpha \qquad (1b)$$

The definition states that the probability of a loss $\mathrm{r_t}$ greater than or equal to VaR over the time horizon T is$1-\alpha$. It also imply that the VaR estimate is a mere quantile that can be produced with the accurate forecast of the cdf. The accurate specification of the cdf depends on the proper estimation of volatility and the assumptions of the underlying distribution of innovations. In our application, we follow the FIAPARCH model under three different distributions: the normal, Student-t, and skewed Student-t distribution innovations.

3.2.2 Fractional integrated APARCH model

Responding to the empirical characteristics of the UAE stock returns, we use FIAPARCH specification to model conditional volatility. The dynamics of the conditional mean is specified as an ARMA(1,1) process[12]. The lag specification was chosen using both AIC and BIC criteria. The ARMA(1,1) model can be defined as follows,

$$r_t = \mu + \psi r_{t-1} + \theta \varepsilon_{t-1}, \quad t \in T \tag{2}$$
$$\varepsilon_t = z_t \sigma_t$$

where $\varepsilon_t = z_t \sigma_t$ follows the FIAGARCH(1,d,1) process and the innovation process z_t can be described by one of the alternative distributional assumptions: the normal, Student-t, and skewed Student-t conditional distributions.

As mentioned previously, the conditional volatility follows FIAPARCH (1,d,1) process, which is specified as:

$$(1-\phi L)(1-L)^d f(\varepsilon_t) = \omega + (1-\beta L)\xi_t \tag{3}$$

where $\xi_t = f(\varepsilon_t) - \sigma_t^\delta$, and $f(\varepsilon_t) \equiv [|\varepsilon_t| - \gamma\varepsilon_t]^\delta$.

As can be seen in Eq. (3), the term $[|\varepsilon_t| - \gamma\varepsilon_t]^\delta$ reflects "leverage" effect, $\gamma \neq 0$. If $0 < \gamma < 1$ then positive innovations increase volatility less than negative innovations. It is vice versa if $-1 < \gamma < 0$. In the case where $\gamma = 0$ positive and negative innovations of same magnitude have the same effect on volatility. Here, δ is a power term parameter. Note also that $|\phi| < 1, \omega > 0$, and that the fractional integration parameter $0 \leq d \leq 1$. Rearranging; Eq. (3) can be written as:

$$\sigma_t^\delta (1-\beta)^{-1}\omega + \lambda(L) f(\varepsilon_t)$$

where $\lambda(L)$is defined as: $\lambda(L) = \sum_{i=1}^{\infty} \lambda_i L^i \equiv [1-(1-\beta L)^{-1}(1-\phi L)(1-L)^d]$. When $d = 0$ the process in Eq. (3) reduces to the APARCH(1,1) model. Also, if $\gamma = 0$ and $\delta = 2$, the process reduces to the FIGARCH (1,d,1) model. This model includes the integrated GARCH as a special case when $d = 1$. For the particular case where $d = 0$, the model shrinks to the famous GARCH model of Bollerslev (1986).

In sum, the FIAPARCH model nests other GARCH-type models with normally standardized innovations. It also allows jointly for volatility clustering, long memory and asymmetry in conditional volatility.

[12] The ARMA (1,1) process is used in order to take into account the serial correlation that are observed in the UAE stock exchanges, as well as to capture the short-memory in the series.

3.2.3 skewed Student-t distribution

In this paper, the values of VaR are going to be computed using FIAPARCH (1,d,1) process. We consider this process under three alternative distributional assumptions: the normal, Student-t, and skewed Student-t conditional distributions. Because of space limitations, only the skewed Student-t distribution will be presented.

The innovation process z_t is said to be standardized skewed Student-t distributed $\left(SKST(0,1,\xi,v)\right)$ if:

$$f(z_t/\xi,v)=\begin{cases}\frac{2}{\xi+\frac{1}{\xi}}\,sg[\xi(sz_t+m|v)] & if\ z_t\geq -m/s\\ \frac{2}{\xi+\frac{1}{\xi}}\,sg[\xi(sz_t+m|\xi/v)] & if\ z_t< -m/s\end{cases} \tag{4}$$

where $g(.;v)$ is the symmetric student density, $v>2$ is the degree of freedom, m is the mean of the non-standardized skewed Student-t, and it can be computed as $m=\frac{\Gamma((v+1)/2)\sqrt{v-2}}{\sqrt{\pi}\Gamma(v/2)}$, s in Eq. (4) stands for the variance of the non-standardized skewed Student-t, it can be calculated as $s=(\xi^2+\xi^{-2}-1-m^2)^{0.5}$. The value of ξ is captured the degree of asymmetry of residual distribution. The density is said to be skewed to the right (left) if $\ln(\xi)>0(<0)$. Therefore, the skewed Student-t distribution is able to account for both heavy tails and skewness in standardized residuals, providing obvious efficiency gains. It nests the Student-t for the normal distribution for $\xi=0$ and $v=\infty$.

In our case, the assumption of conditionally normal distributed innovations is not supported by the data. However, following Bollerslev and Wooldridge (1992) one can estimate GARCH-type models by the Quasi-Maximum Likelihood (QMLE) and obtain robust estimates for the density provided that the model is correctly specified. In this paper, the parameters of the model given by the sample are estimated using a QMLE. The log-likelihood function of $SKST(0,1,\xi,v)$ is given by

$$\begin{aligned}L=T\left\{\ln\Gamma\left(\frac{v+1}{2}\right)-\ln\Gamma\left(\frac{v}{2}\right)-0.5\ln[\pi(v-2)]+\ln\left(\frac{2}{\kappa+\kappa^{-1}}\right)+\ln(s)\right\}\\ -0.5\sum_{t=1}^{T}\left\{\ln(\sigma_t^2)+(1+v)\ln\left[1+\frac{((sz_t+m)^2)}{v-2}\xi^{-2I_t}\right]\right\}\end{aligned} \tag{5}$$

Where $I_t=1$ if $z_t\geq -m/s$ or $I_t=-1$ if $z_t< -m/s$. For a given coefficient of asymmetry ξ, and a given degrees of freedom v, the one-day-ahead VaR is computed for long and short trading positions as $t_{\alpha,v,\xi}\sigma_t$ and $t_{1-\alpha,v,\xi}\sigma_t$, respectively. Here, $t_{\alpha,v,\xi}$ is the lower cutoff point of the skewed Student-t distribution at the $\alpha\%$ significance level. Similarly, $t_{1-\alpha,v,\xi}$ is the corresponding upper cutoff point at the same significance level.

Once the VaR estimates are produced, it is important to evaluate their accuracy to validate the model. If the model used to produce VaR is adequate, then we would expect VaR to be exceeded $\alpha\%$ of the times; also we would expect these exceptions to be serially uncorrelated.

3.2.4 Volatility forecasting

In addition to the classical in-sample model selection criteria, such as the Akaike Information and the Schwarz Bayesian, we use two groups of out-of-sample volatility forecast error statistics. These statistics are used to measure the statistical accuracy of a given model in forecasting the one-day-ahead conditional volatility:

i. The Mincer-Zarnowitz regression: we regress a volatility proxy on out of sample volatility forecasts and observe the coefficient of determination. In our case, this proceeds by estimating the following specification,

$$\hat{\varepsilon}_{t+i}^2 = \varphi_{0+}\varphi_1\hat{\sigma}_{t+i}^2 + \ell_{t+i} \quad (6)$$

where $\hat{\varepsilon}_{t+i}^2$is used as a proxy for the unobservable "true" volatility[13], $\hat{\sigma}_{t+i}^2$is the one-day-ahead projection of the conditional variance under a given specification and, finally ℓ_{t+i} is the error term. Ideally, φ_0 should equal zero and $\varphi_1$should equal one, and the fit should be high[14].

ii. Statistical Loss functions: These include the Mean Squared Error (MSE), the Mean Absolute Percentage Error (MAPE), and the Logarithmic Squared Error (LSE) loss function. The smaller the error statistics, the superior the forecasting model. The loss functions are represented by the following equations:

$$MSE = \frac{1}{2}\sum_{i=1}^{T}(\hat{\varepsilon}_{t+i}^2 - \hat{\sigma}_{t+i}^2)^2 \quad (7)$$

$$MAPE = \frac{1}{2}\sum_{i=1}^{T}\left|\hat{\varepsilon}_{t+i}^2 - \hat{\sigma}_{t+i}^2\right| \quad (8)$$

$$LSE = \frac{1}{2}\sum_{i=1}^{T}\ln\frac{\hat{\varepsilon}_{t+i}^2}{\hat{\sigma}_{t+i}^2} \quad (9)$$

3.2.5. Measure of accuracy for VaR estimates

To evaluate the accuracy of the VaR measure, we use a standard procedure. First, we compute the empirical failure rate for both tails of the distribution. Second, we proceed to test the null that the VaR model is correctly specified using the unconditional coverage test, the LR test hereafter, first proposed by Kupiec (1995). The test statistics is based on the proportion of failures (POF test here after). The test is defined as the number of times a daily return exceeds (in absolute value) the VaR forecast.

The VaR model is correctly specified, if the failure rate is equal to the pre specified VaR level, which is $\alpha\%$. The empirical application here, defines a proportion of failure $POF_{S,}$ for the right tail, in addition to the failure rate $POF_{L,}$ for the left tail. The failure rate is equal to the percentage of positive returns greater than the one-step-ahead VaR calculated for short positions. Similarly, it is defined as the violation rate of the left tail VaR measure for long positions.

To test for the correct specification of the VaR model, define the following hypothesis

$$H_0: POF = \alpha$$
$$H_1: POF \neq \alpha$$

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[13] We used the squared returns as a proxy for the "true" volatility.

[14] The forecast from the volatility model is optimal if we fail to reject the null $H_0: (\varphi_0, \varphi_1) = (0,1)$ and R^2 was high (See for example, Sucarrat, 2008).

Under the null, the POF test is statistically the same as α and hence, the model is correctly specified; whereas, under the alternative the exception rate is statistically more (or less) than α and as a result VaR forecasts are underestimating (or overestimating) market risk. To test the null, Kupiec (1995) has proposed the following test statistics

$$L = -2\ln[(1-\alpha)^{T-x}\alpha^{x}] + 2\ln\left[\left(1-\hat{f}\right)^{T-x}\right]\left(\hat{f}\right)^{x} \qquad (10)$$

where x is the number of times returns exceed (in absolute value) the forecasted VaR in the sample, and T stands for the total size of the evaluation sample. Under the null hypothesis, the limiting distribution of the test statistic has a chi-square distribution with one degree of freedom.

A desirable property of the model is to have independent tail events. In fact, serially correlated exceptions indicate, that the dynamics of return are not captured well by the proposed model. To test for that, we use the dynamic conditional quantile (DCQ here after) test, which is a conditional coverage test that was first proposed by Engle and Manganelli (2004).

In particular, define the deviations of the exceptions from the expected at both tails as $Hit_t(1-\alpha) = I\left(y_t < VaR_t(\alpha)\right) - \alpha$ and $Hit_t(1-\alpha) = I\left(y_t > VaR_t(1-\alpha)\right) - \alpha$. Also define the null $A1$ as: $A1{:}\, E\left(Hit_t(\alpha)\right) = 0$ and $A1{:}\, E\left(Hit_t(1-\alpha)\right)$ =0. A test for the joint hypothesis in $A1$ can be done using the artificial regression: $Hit_t = X\varphi + \varepsilon_t$, where X is a $T \times k$ matrix, and its first column is a column of ones, whereas the next q columns are $Hit_{t-1}, \dots, Hit_{t-q}$, and the remaining $k-q-1$ are additional independent variables including lagged value at risk measures. Under the null hypothesis, the test statistic $\frac{\hat{\varphi}X'X\hat{\varphi}}{\alpha(1-\alpha)} \sim \chi^2(\mathrm{k})$, where $\hat{\varphi}$ is the OLS estimates of $\hat{\varphi}$. We perform the test using the current VaR and five lags of the VaR violations as explanatory variables.

4. Empirical results

4.1 Estimating the models

The analysis begins with the estimation of the ARMA(1,1)-FIAPARCH(1, *d*, 1) model in Equations (2) And (3). The model accounts for serial correlation observed in the levels as well as the power transformations of our time series data. It also captures a possible long memory in the conditional mean and variance. The model is estimated using three different distributions: the Normal, Student-t, and skewed Student-t distributions. The parameters are estimated using Quasi Maximum Likelihood Estimator.

Table (3) reports the estimation results of the model with the Normal, Student-t, and skewed Student-t distributions. In Table (4), we present the specification and diagnostic test results.

Table (3) shows these findings: first, the coefficients $\alpha_1$and β_1 are statistically significant, implying a strong support for ARCH and GARCH effects in the UAE stock exchanges. Second, the fractional differencing parameter (d) is statistically different from zero, and significantly different from unity ($0.2 < d < 0.8$)[15]. These empirical findings support modeling conditional volatility as fractionally integrated and to rule out short memory. Third, the leverage parameter (γ) was not significant for the DFM

[15] However, for the ADSE-normal case, the integration parameter was found significant and above unity,$d = 1.4309$, implies that stock return is neither stationarity nor mean-reverting.

market. Fourth, the exponent coefficient (δ) was significantly greater than unity in both markets. This allows the skewed Student-t modeling for the errors to be more flexible in expressing the relationship between the conditional volatility and past shocks. Finally, ξ and v are significant, so the ex-ante standardized returns of the UAE stock exchanges are leptokurtic and skewed[16]. It also suggests that the skewed Student-t density is suitable for the modeling of return distribution in the UAE stock exchanges.

Table 3: ARMA(1,1)-FIAPARCH(1,*d*,1) parameters estimated

	ADSE			DFM		
	Normal	Student-t	Skewed-t	Normal	Student-t	Skewed-t
μ	0.0157 (0.3387)	0.01952 (0.0841)	0.0298** (0.0363)	0.1243 (0.8057)	0.0295 (0.9530)	0.1232 (0.8118)
ψ	0.2136* (0.0037)	0.2045* (0.0002)	0.1191* (0.0094)	0.3058* (0.0000)	0.2912* (0.0000)	0.2913* (0.0000)
θ	0.1732 (0.0838)	0.26810* (0.0035)	0.2602* (0.0054)	-0.7604* (0.0000)	-0.7639* (0.0000)	-0.7634* (0.0000)
ω	0.0024 (0.0794)	0.01655 (0.1857)	0.0163 (0.1895)	7.0707 (0.1345)	7.4920 (0.0742)	7.9673 (0.0747)
d	1.4309* (0.0000)	0.74582* (0.0000)	0.7474* (0.0000)	0.4594* (0.0000)	0.5224* (0.0000)	0.5156* (0.0000)
α_1	0.2562** (0.0465)	0.2122 (0.0973)	0.2080** (0.0468)	0.3652* (0.0000)	0.3359* (0.0001)	0.3351* (0.0001)
β_1	0.9623 (0.0000)	0.6038* (0.0002)	0.6075* (0.0002)	0.6978* (0.0000)	0.7238* (0.0000)	0.7161* (0.0000)
γ	0.0878 (0.1554)	0.1605* (0.0063)	0.1637* (0.0056)	0.0300 (0.8018)	0.0128 (0.9101)	0.0166 (0.8923)
δ	1.9424* (0.0000)	2.2680* (0.0000)	2.2426* (0.0000)	1.9788* (0.0000)	1.8750* (0.0000)	1.8877* (0.0000)
$v - Student\ t$	-	3.4508* (0.0000)	-	-	10.1842* (0.0000)	-
$\xi - Skewness$	-	-	0.04213** (0.0192)	-	-	0.0294** (0.01743)
$v - Skewness$	-	-	3.4708* (0.0000)	-	-	10.2015* (0.0000)

Notes: * and ** denote significance at the 1% and 5% levels, respectively. The *P*-values are given in parentheses.

Table (4) reports several results. First, the ARMA (1, 1) is sufficient to correct for serial correlation in the conditional mean. Second, the use of asymmetric ARCH class of models seems to be justified. For both series, all asymmetric coefficients were significant at conventional levels. Moreover, both the Akaike (AIC) and Bayesian (BIC) information criteria highlight the fact that the skewed Student-t is a better fit than the Normal and Student-t. In Particular, the skewed Student-t seems to do a good job in describing the dynamic of the second moment of the series, as shown by the Box-Piece statistics of the squared residuals, which were all non-significant at 5% level. Fourth, to confirm the adequacy of the conditional density, we first rely on the adjusted Pearson goodness-of-fit (P) test that compares the empirical distribution with the theoretical one. If the observations are iid and under the null hypothesis of a correct distribution, $P(g)$ is bounded between a $\chi^2(\mathrm{g}-1)$ and a $\chi^2(\mathrm{g}-\mathrm{k}-1)$, where k is the number of estimated

[16] The positive sign of the asymmetric parameter in both markets indicates that the density of the UAE returns is skewed to the right side.

parameters[17]. The results in the table show that the skewed Student-t is particularly successful in modeling the dynamics of the first two conditional moments of the ADSE and DFM returns. Fifth, the Engle and Ng (1993)[18] test statistics was not significant. Similarly are the residual-based diagnostic for conditional heterososkdasticity. The test of Tse (2001) (RBD test) implies that the ARMA (1, 1)-FIAPARCH (1, *d*, *1*) with skewed Student-t distribution captures fully the asymmetric effects of volatility in the ADSE and the DFM returns.

Table 4: Specification tests -models comparison

	ADSE			**DFM**		
	Normal	Student-t	Skewed-t	Normal	Student-t	Skewed-t
Model selection						
Akaike	1.5893	1.4173	1.4166	9.4309	9.4143	9.4123
Schwarz	1.6230	1.4548	1.4388	9.4609	9.4480	9.4228
Dynastic tests						
Skewness	-0.17650*	-0.1995*	-0.1784	0.1045	0.1155	0.1245
	(0.0063)	(0.0022)	(0.0764)	(0.1098)	(0.0771)	(0.0681)
Kurtosis	5.2906*	6.5895*	6.5765*	0.9277*	0.9644*	0.9676*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
J-B	1485.4*	2542.2*	2530.4*	52.761*	57.372*	58.241*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Q(10)$	15.5987**	25.1537*	12.1552	11.3520	12.0124	11.9179
	(0.0484)	(0.0014)	(0.1627)	(0.1825)	(0.1506)	(0.1548)
$Q^2(10)$	7.3369	5.61452	5.3099	7.0300	6.4858	6.3661
	(0.5564)	(0.6903)	(0.8695)	(0.5333)	(0.5929)	(0.6062)
$ARCH(10)$	0.7284	0.5352	0.5246	0.6748	0.6220	0.6097
	(0.6982)	(0.8660)	(0.8737)	(0.4308)	(0.7961)	(0.8067)
$RBD(10)$	87.4839	5.46104	5.3099	6.8016	6.2257	6.0762
	(0.6790)	(0.8583)	(0.8695)	(0.7440)	(0.7955)	(0.8088)
Sign Bias	0.8520	1.1006	1.0317	0.8201	0.8755	0.7329
	(0.3941)	(0.2710)	(0.3021)	(0.4121)	(0.3812)	(0.4635)
Negative Size Bias	0.6189	1.8365	1.8117	0.5433	0.5264	0.4019
	(0.5359)	(0.0662)	(0.0700)	(0.5869)	(0.5985)	(0.6876)
Positive Size Bias	0.4006	0.7844	0.7668	0.1313	0.0631	0.0956
	(0.6887)	(0.4328)	(0.4431)	(0.8955)	(0.9496)	(0.9238)
Joint Test (LM)	1.5170	4.6988	4.4602	0.7998	0.9954	0.9008
	(0.6783)	(0.1952)	(0.2158)	(0.4895)	(0.8023)	(0.8254)
$APGFT(20)$	164.6286*	51.3143	50.4000	21.88	20.514	16.542
	(0.0000)	(0.0895)	(0.1044)	(0.2899)	(0.3642)	(0.6208)

Notes: J-B is the Jarque-Be´ra (1980) normality test statistic. The test follows χ^2distribution with 2 degrees of freedom. ARCH is a test for the conditional heterocedasticity in returns, which is based on the regression of squared residuals on lagged squared residuals. . $Q(10)$ and $Q^2(10)$ are the Box-Pierce statistics of order 10 for remaining serial correlation for respectively standardized and squared standardized residuals. $RBD(10)$ is the residual-based diagnostic test for conditional heterososkdasticity proposed by Tse (2001). For the sign test, negative and positive size bias tests coefficients are displayed; the significance is tested with a standard t-test. The joint test is the Engle-Ng (1993) LM test which is distributed as χ^2. $APGFT(20)$ is the adjusted Pearson goodness-of-fit test (See Palm and Vlaar, 1997). The *P*-values are reported in brackets. * and ** indicate significance at the 1% and 5% levels respectively.

The out-of-sample forecast comparison results for the three density specifications can be seen in Table (5). The statistical loss functions show that, the ARMA (1, 1)-

[17] The statistic is computed as $P(g) = \sum_{i-1}^{g} \frac{(n_i - En_i)^2}{En_i}$ where n_i is the observed number in the sample that fall into i^{th} category and En_i is the number of observations expected to be in the i^{th} category when H_0 is true.

[18] The diagnostic test of Engle and Ng (1993) investigates possible misspecification of the conditional variance equation. The sign bias test examines the impact of positive and negative return shocks on volatility not predicted by the model under construction. The negative size bias test focuses on the different effects that large and small negative return shocks have on volatility, which are not predicted by the volatility model.

FIAPARCH (1, *d*, *1*) model with skewed Student-t has been most accurate. The lowest MSE, MAPE and LSE are obtained when the skewed Student-t distribution for the errors was used. The Minzer-Zarnowitz regression has produced similar results. The lower part of Table (4) shows that the ARMA(1,1)-FIAPARCH(1,*d*,1) with skewed Students-t has significantly provided the most accurate out of sample volatility. These forecasts were efficient as we fail to reject the null hypothesis of optimal forecasts at conventional levels. The coefficient of determination (R^2), of the skewed Student-t distribution yields the highest value[19].

To conclude, the results show that the ARMA–FIAPARCH model with the assumption of skewed Student-t distribution captures the asymmetry, long memory and fat-tails of the ADSE and the DFM returns[20].

Table 5: Empirical forecast evaluations

	ADSE			DFM		
	Normal	Student-t	Skewed-t	Normal	Student-t	Skewed-t
Loss Functions						
MSE	0.2397	0.2374	**0.2338**	0.6341	0.6299	**0.6245**
MAPE	0.4896	0.4872	**0.4835**	0.5145	0.5113	**0.5050**
LSE	0.3704	0.3688	**0.3667**	0.7963	0.7937	**0.7915**
Mincer-Zarnowitz regression						
P-Value	0.0467**	0.0452**	0.0525**	0.0572**	0.0428*	0.0742**
R^2	0.0653	0.0631	0.0722	0.0711	0.0975	0.1202

Note: The upper part of the table reports the statistical loss functions for one-day –ahead conditional variance out-of-sample forecasts. MSE is the mean square error. MAPE is the mean absolute prediction error. LSE is the logarithmic loss function .The lower part of the table reports P-values of the Mincer-Zarnowitz regression test, and the coefficient of determination, R^2. Values in bold refers to the lowest error statistics. *, ** indicate that the null hypothesis $H_0: (\varphi_0, \varphi_1) = (0,1)$ was not rejected at the 5% and 10% significance levels.

4.2 VaR analysis

The paper proceeds to compute out-of-sample VaR using the ARMA(1,1)-FIAPARCH(1,d,1) with Normal, Student-t and skewed Student-t distributions at different tail quantiles[21]. As mentioned previously, if the VaR model is correctly specified, the failure rate should be equal to the pre specified VaR significance level. To assess the relative performance of each model, we used the Kupiec's and the DCQ tests. The results are reported in Table 6 and Table 7 for the two tests respectively. Table 7 presents the results of the DCQ test with $q = 5$ and $k = 7$. The contemporaneous VaR forecasts were included as additional explanatory variable in the test.

The empirical results based on both tests indicate that the VaR model based on the normal distribution has the worst performance in modeling the ADSE and the DFM returns. The left tail results that are relevant to the long position on the index were better than the right tail results. The Student-t model improves the performance compared to the

[19] It is observed that R^2-values are relatively low in all cases. This result is highly consistent with those found in other empirical literature, which are usually lower than 10% (see Andersen and Bollerslev, 1998).
[20] It is worth mentioning here that we also evaluate the ability of other GARCH-type models (e.g. EGARCH, APARCH, FIGARCH, and FIEGARCH) to capture the dynamic behavior of UAE stock markets and we found (the results are not reported) that the FIAPARCH model provides superior performance.
[21] We also estimate the VaR in-sample. The results for this procedure was similar to those obtained from the out-sample procedure. These results are not reported and are only available from the authors.

normal distribution based models; however, its performance is still not satisfactory for both tails. These results show that the skewed Student-t improves considerably on both the normal and Student-t distributions, and for the both tails. This confirms the relevance of the ARMA (1, 1)-FIAPARCH (1, *d*, *1*) model with skewed Student-t distribution for the ADSE and the DFM returns. Thus, we conclude that the skewed Student-t distribution tends to give the most correct estimates of VaR values in the UAE stock exchanges.

Table 6: Kupiec test of VaR Estimates

Short position				Long position			
α Quantile	Failure rate (f_s)	Kupiec	*P*-value	α Quantile	Failure rate (f_L)	Kupiec	*P*-value
ADSE							
Normal FIAPARCH(1,d,1)							
0.95	0.95000*	-5.6e-014	1.00000	0.05	0.025000**	6.39790	0.01142
0.975	0.95750**	4.1678	0.041200	0.025	0.017500**	4.02960	0.03102
0.99	0.97250*	8.3797	0.003794	0.01	0.015000	0.87570	0.34938
0.995	0.98000*	10.272	0.001351	0.005	0.010000	1.55520	0.21236
0.9975	0.98250*	15.333	9.0108e-005	0.0025	0.010000**	5.11300	0.02374
Student-t FIAPARCH(1,d,1)							
0.95	0.92750	3.7655	0.05231	0.05	0.042500	0.49798	0.48039
0.975	0.96000	3.1329	0.07672	0.025	0.015000	1.91100	0.16685
0.99	0.98000	3.1309	0.07682	0.01	0.007500	0.27643	0.59905
0.995	0.99000	1.5552	0.21236	0.005	0.005000	0.00900	1.00000
0.9975	0.99500	0.7751	0.37864	0.0025	0.002500	0.00130	1.00000
Skewed-t FIAPARCH(1,d,1)							
0.95	0.93000	3.01210	0.08264	0.05	0.050000	0.00684	1.00000
0.975	0.96750	0.84461	0.35808	0.025	0.027500	0.09939	0.75250
0.99	0.98500	0.87570	0.34938	0.01	0.015000	0.87570	0.34938
0.995	0.99250	0.43531	0.50940	0.005	0.005000	0.00710	1.00000
0.9975	0.99631	0.63360	0.38180	0.0025	0.005000	0.77510	0.37864
DFM							
Normal FIAPARCH(1,d,1)							
0.95	0.96133**	4.19240	0.013869	0.05	0.038667	2.19240	0.13869
0.975	0.97867*	5.43490	0.010956	0.025	0.020000*	6.82489	0.00363
0.99	0.99067*	8.03440	0.008527	0.01	0.008000*	13.3253	1.5684e-003
0.995	0.99333*	13.3789	1.5381e-003	0.005	0.006666*	21.3789	1.5381e-005
0.9975	0.99733*	19.0081	1.9279e-005	0.0025	0.005333*	23.8175	1.1776e-007
Student-t FIAPARCH(1,d,1)							
0.95	0.96400	3.41480	0.06461	0.05	0.038667	2.19240	0.13869
0.975	0.98133	1.35100	0.24511	0.025	0.023000	2.85120	0.09130
0.99	0.99333	0.95376	0.32876	0.01	0.009000	0.32531	0.56844
0.995	0.99467	2.86660	0.09043	0.005	0.004300	0.16189	0.68742
0.9975	0.99731	1.30311	0.26024	0.0025	0.002233	0.49381	0.48223
Skewed-t FIAPARCH(1,d,1)							
0.95	0.95267	2.76650	0.09625	0.05	0.049000	1.69010	0.19359
0.975	0.97433	1.35100	0.24511	0.025	0.024730	2.02270	0.15496
0.99	0.99033	0.95376	0.32876	0.01	0.009700	0.32531	0.56844
0.995	0.99567	2.86660	0.09043	0.005	0.004833	0.01639	0.89812
0.9975	0.99760	1.01120	0.30248	0.0025	0.002393	0.49381	0.48223

Note: *P*-values for the null hypotheses $f_L = 1 - \alpha$ (i.e. failure rate for the long trading positions is equal to 1- α, right of the table) and $f_s = \alpha$ (i.e. failure rate for the short trading positions is equal to α, left of the table). α is equal respectively to 0.05, 0.025, 0.01, 0.005 and 0.0025. * and ** indicate a significance at the 1% and 5% levels, respectively

Table 7: DCQ tests of VaR estimates

Short position			Long position		
α Quantile	Statistics	P-value	α Quantile	Statistics	P-value
ADSE					
Normal FIAPARCH(1,d,1)					
0.95	3.5425	0.83071	0.05	9.8877	0.19503
0.975	11.042	0.13681	0.025	17.593**	0.01395
0.99	25.587*	0.00059	0.01	52.974*	3.7508e-009
0.995	43.137*	3.1385e-007	0.005	48.962 *	2.3086e-008
0.9975	45.076*	1.3216e-007	0.0025	102.72*	0.00000
Student-t FIAPARCH(1,d,1)					
0.95	6.4951	0.48327	0.05	14.4348**	0.01900
0.975	12.3870	0.08851	0.025	11. 5723	0.08718
0.99	18. 6496*	0.00112	0.01	0.35289	0.99983
0.995	2. 3720	0.91542	0.005	0.75946	0.99784
0.9975	1.6569	0.97638	0.0025	0.77609	0.99768
Skewed-t FIAPARCH(1,d,1)					
0.95	6.1606	0.52113	0.05	6.3318	0.50158
0.975	5.7442	0.56991	0.025	3.9269	0.78816
0.99	1.8165	0.96929	0.01	5.6140	0.28890
0.995	0.6891	0.99842	0.005	0.7725	0.99771
0.9975	1.0025	0.99479	0.0025	2.5001	0.92709
DFM					
Normal FIAPARCH(1,d,1)					
0.95	15.4159*	2.6093-e006	0.05	17.7091*	1.3589e-003
0.975	110.217*	5.1766-e006	0.025	26.7593*	4.4543e-003
0.99	111.9820*	0.00000	0.01	33.6196*	6.9988e-005
0.995	118.6077*	0.00000	0.005	51.5093*	2.9819e-007
0.9975	117.9036*	0.00000	0.0025	74.1410*	1.7634e-009
Student-t FIAPARCH(1,d,1)					
0.95	5.6898	0.57640	0.05	7.73300	0.35672
0.975	5.5603	0.59193	0.025	6.70710	0.46000
0.99	5.2607	0.62818	0.01	0.64833	0.99870
0.995	4.6253	0.70558	0.005	0.44401	0.99963
0.9975	1.8797	0.96620	0.0025	1.07160	0.99359
Skewed-t FIAPARCH(1,d,1)					
0.95	3.9774	0.78238	0.05	7.12860	0.41562
0.975	3.6310	0.82116	0.025	9.00280	0.25245
0.99	5.2713	0.62689	0.01	0.65982	0.99863
0.995	4.5294	0.71718	0.005	0.81040	0.99734
0.9975	1.8797	0.96620	0.0025	1.10660	0.99292

Note: P-values for the dynamic quantile test statistic $\frac{\hat{\varphi}X'X\hat{\varphi}}{\alpha(1-\alpha)} \sim \chi^2(k)$. The test statistics for the long trading positions is test at quintile 1- α, right of the table while α is used to test for the short trading positions, left of the table. α is equal respectively to 0.05, 0.025, 0.01, 0.005 and 0.0025. * and ** indicate a significance at the 1% and 5% levels, respectively.

5. Conclusions

The paper model, measure and forecast VaR in the UAE stock exchanges using an ARMA-FIAPARCH model. The model was evaluated with three alternative distributions and in terms of its ability to produce accurate VaR measures. We found that the FIPARCH model with skewed Student-t distribution provides the best fit for the UAE stock exchanges. Other distributional assumptions, normal and t, were found to be inferior. The same model with Skewed-t distribution was also found more accurate in out of sample forecasting of VaR. The reason for the appropriateness of the model is that it gathers all the empirical features observed in the UAE stock returns.

The results of the paper provide an important implication to investors and risk managers. It shows that advanced financial techniques that catch long memory, asymmetry and fat tails in equity returns are necessary for accurate and correct estimation of risk in the UAE stock exchanges. The static econometric models that ignored these characteristics have produced inferior results.

Three particular limitations and future studies could be followed to improve this study. First, our empirical results are based on the UAE markets indices. So, it would be interesting to assess the VaR's performance on arbitrary portfolios which may provide more information about UAE markets risk to investors. Second, it would be interesting to evaluate the predictive accuracy of other forecasting models including the realized volatility (i.e. estimated from high frequency intra-day data). Finally, it would helpful to assess the VaR's performance based on other time horizons (i.e. 5, 20, 60- and 100-day-ahead time horizons).

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